Mechanical Systems and Signal Processing 101 (2018) 549–574

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Real time damage detection using recursive principal components and time varying auto-regressive modeling

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ARTICLE INFO

Article history:
Received 21 February 2017
Received in revised form 21 July 2017
Accepted 22 August 2017

Keywords:
Recursive Principal Component Analysis (RPCA)
Time-Varying Autoregressive Modeling (TVAR)
Damage Sensitive Features (DSF)

ABSTRACT

In this paper, a novel baseline free approach for continuous online damage detection of multi degree of freedom vibrating structures using Recursive Principal Component Analysis (RPCA) in conjunction with Time Varying Auto-Regressive Modeling (TVAR) is proposed. In this method, the acceleration data is used to obtain recursive proper orthogonal components online using rank-one perturbation method, followed by TVAR modeling of the first transformed response, to detect the change in the dynamic behavior of the vibrating system from its pristine state to contiguous linear/non-linear-states that indicate damage. Most of the works available in the literature deal with algorithms that require windowing of the gathered data owing to their data-driven nature which renders them ineffective for online implementation. Algorithms focussed on mathematically consistent recursive techniques in a rigorous theoretical framework of structural damage detection is missing, which motivates the development of the present framework that is amenable for online implementation which could be utilized along with suite experimental and numerical investigations. The RPCA algorithm iterates the eigenvector and eigenvalue estimates for sample covariance matrices and new data point at each successive time instants, using the rank-one perturbation method. TVAR modeling on the principal component explaining maximum variance is utilized and the damage is identified by tracking the TVAR coefficients. This eliminates the need for offline post processing and facilitates online damage detection especially when applied to streaming data without requiring any baseline data. Numerical simulations performed on a 5-dof nonlinear system under white noise excitation and El Centro (also known as 1940 Imperial Valley earthquake) excitation, for different damage scenarios, demonstrate the robustness of the proposed algorithm. The method is further validated on results obtained from case studies involving experiments performed on a cantilever beam subjected to earthquake excitation; a two-storey bench-scale model with a TMD and, data from recorded responses of UCLA factor building demonstrate the efficacy of the proposed methodology as an ideal candidate for real time, reference free structural health monitoring.

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http://dx.doi.org/10.1016/j.ymssp.2017.08.037
0888-3270/

Nomenclature

x	displacement vector
V	mode shape matrix
Q	modal coordinate matrix
R	covariance matrix
Ψ	Principal Orthogonal Coordinate Matrix
ε, γ	error term
R_k	covariance matrix at k^{th} time instant
Υ	diagonal matrix of eigenvalues of covariance matrix
W	matrix of eigenvectors of covariance matrix
$\widetilde{\psi}$	POC estimate vector
H_k	matrix of eigenvectors of the middle term at k^{th} instant
λ_k	diagonal matrix of eigenvalues of the middle term at k^{th} instant
α_i	Eigen value corresponding to i^{th} eigenvector
W_k^1	Eigen subspace at k^{th} time instant that accounts for more than 90% kinetic energy
W_k^2	Eigen subspace at k^{th} time instant that accounts for remaining kinetic energy
a_1, a_2	time varying AR coefficients
P_w	covariance matrix of process noise
b, C, γ	Kalman state variables
μ_{a_i}	recursive mean of a_i^{th} coefficient
ζ_{a_i}	recursive sixth moment of a_i^{th} TVAR coefficient
κ	term controlling level of non-linear force
z, Q, A, β	bouc-wen parameters

List of Acronyms

PCA	Principal Component Analysis
POC	Principal Orthogonal Component
POM	Proper Orthogonal Mode
POV	Principal Orthogonal Values
EVD	Eigen Value Decomposition
RPCA	Recursive Principal Component Analysis
TVAR	Time Varying Auto Regressive
DSF	Damage Sensitive Features
RRE	Recursive Residual Error
dof	Degree of Freedom
SHM	Structural Health Monitoring
FOP	First Order Perturbation
KPCA	Kernel Principal Component Analysis
KG	Kalman Gain
sdof	Single Degree of Freedom
mdof	Multi Degree of Freedom
AR	Auto Regressive
UCLA	University of California Los Angeles
UCLAFB	UCLA Factor Building
SMF	Special Moment Resisting Steel Frame
TMD	Tuned Mass Dampers

1. Introduction

Structural damage detection involving condition assessment, fault diagnosis and prognosis of civil, mechanical and aerospace infrastructure has garnered significant attention and a wealth of literature exists in this area [1–3]. Largely premised on the idea that damages manifest themselves through the alteration of structural dynamic properties such as natural frequency, modeshapes, damping; a significant number of algorithms and methodologies have been proposed in recent times [4–7]. Damages mostly occur due to higher operational loads, excessive response, propagation of cracks, buckling, fatigue, impact of a foreign object, etc. An ideal damage detection framework should provide detection in near real time, identify the presence of damage and its location and estimate the severity of the damage in the structure. Currently available damage detection schemes [4–6] are mostly offline in nature and data processing usually happens in batch mode; hence, the development of online damage detection techniques based on processing of response that streams in real time, still remains a challenge. Traditional offline damage detection schemes have disadvantages mostly due to their inherent dependence on